Does Knowledge Accumulation Increase the Returns to Collaboration?

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Abstract

We report results from the first causal test of the knowledge burden hypothesis, one of several theories advanced to explain increasing team sizes in science. For identification, we exploit the collapse of the USSR as an exogenous shock to the knowledge frontier causing a sudden release of previously hidden research. We report evidence that team size increased disproportionately in Soviet-rich relative to -poor subfields of theoretical mathematics after 1990. Furthermore, consistent with the hypothesized mechanism, scholars in Soviet-rich subfields disproportionately increased citations to Soviet prior art and became increasingly specialized.

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1 Introduction

Research teams are growing in size (Jones, 2011). Several theories explain the rise in collaboration, including the accumulation of knowledge (Jones, 2009), declining communication costs (Agrawal and Goldfarb, 2008; Kim et al, 2009), increasing capital intensity, shifting authorship norms, and increasing returns to research portfolio diversification (Stephan, 2012). These different explanations yield distinct policy implications regarding, for example, subsidies to higher education and the composition of research evaluation committees (Jones, 2010).

We examine whether knowledge accumulation leads to increased collaboration and report evidence consistent with Jones' (2009) burden of knowledge hypothesis. While we do not rule out other explanations as possible additional drivers of the increasing rate of collaboration, we document that a shock to the knowledge frontier led to increased collaboration and specialization. Specifically, we examine whether the sudden and unexpected increase in knowledge of theoretical mathematics that came with the fall of the Soviet Union led to an increase in collaboration among non-Soviet scholars. Using an identification strategy inspired by Borjas and Doran (2012), we categorize as "Soviet-rich" those subfields of theoretical mathematics where Soviet mathematicians made a high contribution relative to mathematicians from other nations before the collapse of the Soviet Union.

We find that collaboration rose disproportionately in Soviet-rich relative to -poor fields after 1990. Furthermore, consistent with the hypothesized mechanisms, researchers in Soviet-rich subfields disproportionately increased their citations to Soviet prior art as well as their degree of specialization after 1990, relative to researchers in Soviet-poor subfields. Moreover, the knowledge shock is followed by a disproportionate increase in researcher team size in Soviet-rich subfields in Japan, a region that did not experience a large influx of Soviet immigrants, suggesting the estimated effect is not caused by an increase in labor market competition. We interpret these findings as consistent with the theory that an outward shift in the knowledge frontier leads to an increase in the returns to collaboration and specialization.

Several prior studies present evidence that the size of research teams has increased steadily over time (Adams et al, 2005; Wuchy et al, 2007; Jones, 2009). For example, Wuchy et al (2007) show that over the latter half of the twentieth century, team size increased in 170 of 171 fields in science and engineering, 54 of 54 fields in the social sciences, and 24 of 27 fields in the arts and humanities. Furthermore, this increase even occurred in fields traditionally associated with individual-oriented research: "Surprisingly, even mathematics, long thought the domain of the loner scientist and least dependent of the hard sciences on lab scale and capital-intensive equipment, showed a marked increase in the fraction of work done in teams, from 19% to 57%, with mean team size rising from 1.22 to 1.84." Moreover, they present citation-based evidence that the relative impact of team versus individual output is increasing over time, even after controlling for self-citations.

Scholars have advanced a number of hypotheses to explain this trend. Hesse et al (1993) and others emphasize the role of reduced communication costs due to advances in communication technology (Agrawal and Goldfarb, 2008; Kim et al, 2009) or reductions in the cost of travel. Stephan (2012) discusses several more alternatives. For example, increasing capital intensity in many fields, such as the role of particle accelerators in physics, may increase the returns to collaboration due to the indivisibilities of research equipment. Changing norms may mean that contributors who in the past would have been listed in the acknowledgements are increasingly likely to be included as coauthors, especially in lab-based sciences. Academics also may find increasing returns to mitigating publication risk by diversifying their research portfolios as publication requirements for promotion and tenure rise.

Jones (2009) emphasizes the "knowledge burden" hypothesis in which successive generations of innovators face an increasing education burden due to the advancing knowledge frontier. This advancing frontier, he posits, requires innovators to specialize more and thus necessitates working more collaboratively, which alters the organization of innovative activity towards teamwork. Jones provides descriptive statistics consistent with this theory. For example, he shows that over time: 1) the number of co-authors on academic publications increases, 2) Nobel laureates are older when they perform their great achievement, 3) the number of co-inventors per patent increases, 4) the age at first innovation increases, and 5) the probability of switching fields decreases. However, these statistics are also consistent with some of the other explanations.

While the various explanations are not mutually exclusive, it is important to determine whether knowledge accumulation does in fact influence the propensity to collaborate and specialize, since this raises specific policy implications that do not apply under the alternate explanations. For example, Jones (2011) presents a model in which the knowledge burden leads to a poverty trap. As the knowledge frontier shifts outwards, individuals compensate by specializing, and thus the returns to collaborating increase. However, in economies where the market for complementary skills is thin, individuals are less likely to invest in the human capital necessary to reach the frontier. This results in an increasingly thin market for specialized skills and thus further lowers the returns to human capital acquisition (creating a trap). Therefore, one policy prescription is to subsidize skills development in a concentrated area (e.g., infectious diseases) in order to address the complementary skills shortage for a finite period of time until the private returns to acquiring specialized skills are sufficient for the labor market to sustain the cycle without further intervention. This policy initiative is not appropriate if knowledge accumulation does not increase the returns to collaboration and the observed rise in team size is driven by other factors in the economy, such as rising capital costs and/or falling communication costs.

In a separate paper, Jones (2010) proposes policies involving changes to the way ideas are evaluated. If research teams, rather than individuals, are needed to work on scientific problems due to an outward–shifted knowledge frontier, then perhaps teams rather than individuals are needed to evaluate grant applications. Again, this policy prescription is not relevant if the observed increase in team size is not due to knowledge accumulation but rather other factors. For example, if team size is increasing due to rising capital costs, then this does not imply increasing returns to team-based evaluation since the equipment is not required for evaluating the grant proposal. Jones also proposes increased subsidies for individuals who enter into science careers since, under the knowledge accumulation hypothesis, researchers bear increasing private costs to reach the frontier. Again, this policy prescription is not appropriate if the observed rise in collaboration is due to other factors.

Therefore, these policy implications suggest that identifying a causal relationship between an outward shift in the knowledge frontier and an increase in the propensity to collaborate, separately from other explanations for increasing collaboration, is important. However, identification is difficult because many unobservables may be (and likely are) correlated with both collaborative behavior as well as the march of time. In order to provide more compelling evidence that an outward shift in the knowledge frontier leads to a growing propensity to collaborate, we need an instrument that is correlated with a shift in the knowledge frontier but not with collaboration except indirectly through its effect on the frontier.

The collapse of the Soviet Union in 1989 provides such an instrument.[1] Although the USSR was a world leader in various subfields of mathematics, Communist government officials forced their researchers to work in isolation from the rest of the world. For example, with few exceptions, scholars were prohibited from traveling, publishing outside of the Soviet Union, and accessing foreign publications without case-by-case government approval. Thus, when the Iron Curtain fell and Soviet science became widely available, the knowledge frontier in mathematics outside the USSR experienced a shock.

[1]We follow in a long tradition of papers that employ political shocks as an instrument to understand changes in knowledge production, knowledge dissemination, and growth. Other recent papers that use this empirical strategy include, for example, Waldinger (2010, 2012), Fons-Rosen (2012), Stuen, Mobarak, and Maskus (2012), Jones and Olken (2005), and Acemoglu, Hassan, and Robinson (2011). Our specific identification strategy exploits the same political shock as Borjas and Doran (2012, 2013a, 2013b). Their research examines the impact of the collapse of the Soviet Union on the rate of output of American and Soviet mathematicians and on the type of research done by American mathematicians, comparing Soviet-rich and Soviet-poor fields of mathematics. We exploit the same variation across fields to study a different question, emphasizing the impact on knowledge flows rather than labor market flows.

Furthermore, the degree of the knowledge shock across subfields of mathematics varied. Borjas and Doran (2012) show that the Soviet mathematics community was very advanced relative to the West in some subfields of theoretical mathematics, such as partial differential equations and operator theory, and much less so in others, such as abstract harmonic analysis as well as sequences, series, and summability.

Focusing on theoretical mathematics, we exploit this variation in the degree of knowledge shock across subfields using a difference-in-differences type of analysis. Specifically, we compare the propensity of mathematicians working outside the USSR to collaborate in Soviet-rich versus -poor subfields before and after the shock. We do this using 41 years of publication data in theoretical mathematics covering the period 1970-2010, 20 years before and after the collapse of the Soviet Union.

We categorize papers using the internationally recognized Mathematics Subject Classification codes developed and assigned by the Mathematical Reviews division of the American Mathematical Society. We follow the Soviet-rich versus -poor subfield classification developed by Borjas and Doran (2012), which they base on the fraction of publications produced by Soviet researchers during the period 1984-1989. We then focus our attention on mathematicians working outside the USSR and drop observations that involve collaboration with Soviet researchers.

Based on a simple comparison of means, we report that team size - the number of coauthors on a paper - increased after the fall of the Iron Curtain, in both Soviet-rich and -poor subfields. However, consistent with the theory, team size grew disproportionately more in Soviet-rich subfields after the shock. Specifically, we calculate the mean team size before and after the collapse of the Soviet Union. For the "treated" subfields (Soviet-rich), the mean team size for the 20-year period before 1990 was 1.34 compared to 1.78 for the 20-year period after. By comparison, for the control subfields (Soviet-poor), the mean team size was 1.26 before compared to 1.55 after. These differences in means suggest a disproportionate increase in team size for Soviet-rich subfields after the collapse of the Soviet Union (Figure 1). The mean team size for Soviet-rich subfields was just 6% higher than for Soviet-poor before 1990, but 15% higher after. This finding is consistent with the knowledge burden effect.

However, there may be systematic differences between Soviet-rich and -poor subfields that are not accounted for when comparing these simple means. Therefore, we turn to our difference-in-differences estimation to study the relationship further. We find evidence of an 8% disproportionate increase in collaboration for Soviet-rich subfields after the collapse of the Soviet Union. This result is robust to various definitions of Soviet-rich versus -poor subfields. Pre-existing time trends do not drive these results: We show that the disproportionate increase in team size in Soviet-rich fields did not begin until shortly after 1990. It is difficult to explain this result with the alternate theories. For example, there is no obvious reason why communication costs were disproportionately lowered in 1990 for non-Soviet researchers in Soviet-rich versus -poor subfields. Similarly, it is difficult to conceive of an increase in capital costs that disproportionately affected researchers in Soviet-rich versus -poor fields after 1990 but not before. In other words, to be consistent with this finding, a theory must explain why team size increased disproportionately for these particular subfields (Soviet-rich) and at this particular time (after 1990, without a pre-trend).

Next, we examine evidence of the underlying mechanism associated with the knowledge burden hypothesis. First, analyzing citation data, we find that authors in Soviet-rich fields disproportionately increased their propensity to draw upon Soviet knowledge after 1990. This is fully consistent with our knowledge flow interpretation. Second, we find evidence of an increase in researchers' specialization in Soviet-rich relative to -poor subfields after the fall of the Soviet Union. To do this, we employ an author-level measure of specialization based on the number of fields in which that author published. We observe an increased tendency for authors publishing in Soviet-rich subfields to specialize (relative to authors publishing in Soviet-poor subfields) after the collapse of the Iron Curtain.

Another explanation for the increased collaboration in mathematics after the fall of the Soviet Union is that the influx of Soviet mathematicians to American and European universities (documented in Borjas and Doran, 2012, 2013a, 2013b) increased competition for jobs and journal slots. We believe our results more likely are driven by an outward shift in the knowledge frontier for four reasons. First, we drop all papers with Soviet authors from our main specifications. Second, we show that papers in Soviet-rich subfields disproportionately cited Soviet papers after the fall of the Soviet Union, suggesting that non-Soviet scholars did indeed draw upon the insights of Soviet mathematicians; also, the changes in these subfields were disproportionately influenced by Soviet knowledge rather than Soviet scholars (especially given that non-Soviet scholars wrote the focal papers). Third, we report evidence of increased specialization in Soviet-rich fields, consistent with the direct mechanism described in Jones (2009). Last, and perhaps most importantly, we show the same patterns persist even when restricting our attention to journals local to Japan, a country that was not a destination choice for Soviet scholars, still recognizing that the field is subject to a global labor market.

We structure the remainder of the paper as follows. In Section 2, we provide historical context for our instrument, explaining how knowledge was developed in the Soviet Union and yet kept secret from Western mathematicians, creating the conditions for the 1990 shock to the frontier. In Section 3, we describe our differences-in-differences empirical strategy by comparing the propensity to collaborate in Soviet-rich versus -poor subfields before and after the knowledge shock. In Section 4, we describe the mathematics publication data we use to construct our sample as well as the method we employ for classifying subfields as Soviet-rich or -poor. We present our results in Section 5 and our conclusions in Section 6.

2 Historical Context

Our empirical strategy relies on the assertion that the collapse of the Soviet Union around 1990 caused an outward shift in the knowledge frontier in mathematics and that it did so more for some subfields than others. We rely on three observations to substantiate this assertion: 1) the Soviet Union's effect on the knowledge frontier in mathematics was significant, 2) the Soviet Union's effect on the knowledge frontier was greater in some subfields than others, and 3) the knowledge produced in the Soviet Union was kept secret from the outside world such that its effect on the frontier came reasonably suddenly in the years following 1990. We offer historical context for each of these three points below.

The first observation is that the Soviet Union's contribution to knowledge in the field of mathematics was meaningful and significant. The Soviet Union was and Russia continues to be a world-renowned center of scientific research, with mathematics holding a prominent position. Lauren Graham, a historian of Soviet science and technology, states: "Of all fields of knowledge, it was mathematics to which Russia and the Soviet Union made the greatest contributions. The Soviet Union became a world power in mathematics" (Graham, 2008). Graham attributes the Soviet Union's strength in scholarly research in mathematics to the fact that it attracted great minds; mathematics was uniquely detached from politics, conferred status and prestige, and offered financial rewards superior to many other occupations.

The second observation is that the Soviet Union's contribution to knowledge was significantly greater in some subfields of mathematics than others. Borjas and Doran (2012) show this empirically by comparing across subfields the fraction of Soviet-to-American papers published during the period 1984-1989. We provide further evidence below by comparing the fraction of Soviet-to-non-Soviet papers published worldwide during the period 1970-1989. Graham (1993) notes that although Soviet mathematicians were strong across the entire spectrum of theoretical and applied mathematics, they seemed to have made the greatest advancements, relative to the rest of the world, in pure theory. One explanation for this is politics. Soviet policies were strict about secrecy and focused on maintaining control over technological developments. It was easier for Soviet mathematicians to build on their progress in pure theory than in areas where technology implementation was more immediate. Many advances in applied mathematics were stalled for political reasons, with exceptions linked to government interests such as the space program (Graham, 1993). Differences in subfields were further amplified due to path dependency: Subfields that attracted bright minds early on were more likely to subsequently attract more bright minds due to mentorship opportunities (Borjas and Doran, 2012). The importance of mentorship is well known in science (Merton, 1973) and was likely particularly salient in this setting due to restrictions on travel and access to foreign journals. For example, the success of Moscow mathematics can be traced back to Ergorov and his student N. N. Luzin (Tikhomirov, 2007). Luzin, whose famous work was mainly focused on the theory of functions, a subfield of theoretical mathematics, mentored subsequent generations of eminent Soviet mathematicians. On the other hand, little outstanding mentorship was available to practitioners of some other subfields of theoretical mathematics, like algebraic geometry (Borjas and Doran, 2012).

The third observation is that the knowledge produced in the Soviet Union was kept secret from the outside world such that its effect on the frontier came reasonably suddenly in the years following 1990. Soviet researchers were prevented from publishing their findings, traveling to conferences, communicating or collaborating with non-Soviets, and even accessing non-Soviet references. The Communist government kept strict control on international travel. Academics who wished to attend foreign conferences had to go through a stringent and lengthy approval process, with many researchers blacklisted because of "tainted" backgrounds. The few approvals granted were typically for travel in Eastern Europe (Ganguli, 2011). Furthermore, Soviet advancements in mathematics remained relatively unknown in the United States until the collapse of the Soviet Union mainly because the USSR government kept much of Soviet science secret (Graham and Dezhina, 2008). In addition, what escaped the secrecy filter was subject to the natural barrier imposed by the Russian language. Graham and Dezhina (2008) note: "the Russian language was known by few researchers outside the Soviet Union, and consequently the achievements of Soviet researchers were more frequently overlooked than those presented in more accessible languages." Borjas and Doran (2012) provide extensive evidence that Soviet knowledge in mathematics was not known in the West, although translations of some Soviet scientific journals were available before the collapse of the Soviet Union.

The limited diffusion of Soviet mathematics into the West is evident in the aftermath of the collapse of the Soviet Union. Starting in 1990, Soviet discoveries began to spread through the West and were considered new and important. Communication and travel restrictions were lifted, publications were translated and indexed, and ideas and knowledge began to flow out from the former Soviet Union into the broader research community. The following quotes by Harvard mathematician Persi Diaconis (from an article published on May 8, 1990 in the *New York Times*), provides an indication of the sudden outward shift of the knowledge frontier: *"It's been fantastic. You just have a totally fresh set of insights and results." Dr. Diaconis said he recently asked Dr. Reshetikhin for help with a problem that had stumped him for 20 years. "I had asked everyone in America who had any chance of knowing" how to solve a problem of determining how organized sets become disorganized, Dr. Diaconis said. No one could help. But Dr. Reshetikhin told Dr. Diaconis that Soviet scientists had done a lot of work on such problems. "It was a whole new world I had access to," Dr. Diaconis said.*

To be clear, for our identification strategy to work, we do not require there to have been no information leaking out of the Soviet Union prior to 1990. Instead, we require the knowledge available to non-Soviet researchers to have increased after 1990 in Soviet-rich relative to Soviet-poor fields.

In sum, the fall of the Iron Curtain provides a plausible natural experiment differentially affecting the knowledge frontier across subfields of theoretical mathematics. This historical event was exogenous to the mathematics research community and set free a large pool of accumulated knowledge. Furthermore, Borjas and Doran (2012), who pioneered the use of this event as an instrument for causal identification in the setting of mathematics, present comprehensive evidence indicating that the timing of the collapse took the global mathematics community by surprise; even in the late 1980s, both the Western mathematical community and Soviet scholars were quite certain that Soviet mathematics would remain secluded for the foreseeable future.

3 Estimation Strategy

We employ a difference-in-differences estimation strategy in which we compare collaboration rates in subfields where the knowledge frontier was most affected by Soviet knowledge (treated) with subfields least affected (control), both before and after the fall of the Iron Curtain (1990). In other words, we examine the difference between treated and control subfields in two periods, before and after the treatment. Thus, we distinguish between the rise in team size that is directly attributable to the shift in the knowledge frontier from the underlying differences between treated and control subfields as well as the underlying changes in collaboration patterns in theoretical mathematics over time.

The objective of our empirical analysis is to estimate the effect of the knowledge shock on collaboration, which we measure as a count of the number of unique authors on a publication. Thus, we estimate the following linear regression model, using the academic paper as our unit of analysis:

$$TeamSize_{it} = \beta(SovietRich_i \times AfterIronCurtain_t) + Subfield_i + \gamma_t + \epsilon_{it} \quad (1)$$

$TeamSize_{it}$ is the count of authors for each academic paper i published in year t. $SovietRich_i$ is an indicator variable equal to 1 if academic paper i belongs to the treated group and 0 otherwise. $AfterIronCurtain_t$ is an indicator variable equal to 1 if academic paper i is published after 1990 and 0 otherwise. This applies to academic papers in both treated and control subfields. We include subfield and time fixed effects. Hence, the main effects $SovietRich_i$ and $AfterIronCurtain_t$ drop out of the estimating equation.

We are primarily interested in the estimated coefficient on the interaction between $SovietRich_i$ and $AfterIronCurtain_t$, which equals 1 for publications in treated subfields that were published after the knowledge shock and 0 for all others. We interpret a positive estimated value of this coefficient as implying that the average team size of Soviet-rich subfields increased disproportionately, relative to Soviet-poor subfields, after the knowledge shock, consistent with the knowledge frontier theory. After establishing this relationship, we provide evidence consistent with a mechanism driven by an outward shift in the knowledge frontier.

4 Data

We next describe the three main steps we follow to collect and prepare our data set. First, we extract publication data, then we rank subfields in mathematics with respect to the relative contribution by Soviets, and finally we process the data for analysis.

4.1 Data Collection

We collect data on every publication in theoretical mathematics published during the 41-year period 1970 – 2010. This represents 20 years of data both before and after the collapse of the Soviet Union in 1990. We follow Borjas and Doran's (2012) interpretation of historical events that isolates 1990 as the year when academic seclusion was significantly lessened. We recognize that the political and social turmoil preceding and following the fall of the Iron Curtain spanned a period of roughly three years, between 1989 and 1991. Our results are robust to choosing 1989 or 1991 as the cutoff rather than 1990.

We collect these data from the American Mathematical Society (AMS). The Mathematical Reviews (MR) division of AMS maintains a comprehensive bibliographic database of worldwide academic publications in mathematics. The MR database includes all mathematics-related journal publications covering the three main categories of mathematics: mathematical foundations (including history and biography), pure or theoretical mathematics, and applied mathematics. Our focus is on theoretical mathematics, which includes analysis, algebra, and geometry (Figure 2).

4.2 Classification

Our empirical strategy relies on exploiting variation in the degree to which the knowledge frontier was shifted outwards as a result of the collapse of the Soviet Union. Specifically, we distinguish between subfields of theoretical mathematics where the Soviets were particularly strong in the years prior to the collapse versus subfields where they were less strong. Borjas and Doran (2012) created this identification tool; we directly employ their insight on how to classify these data to distinguish between Soviet-rich and -poor.

We rely on the careful and exhaustive work of the MR division, which classifies each paper in mathematics using Mathematics Subject Classification (MSC) codes. The MSC schema is used internationally and facilitates targeted searches on research subjects across all subfields of mathematics. The MR team assigns precisely one primary MSC code to each academic publication uploaded to the MR database. The theoretical mathematics group is comprised of a total of 40 active primary MSC codes (14 algebra, 19 analysis, 7 geometry). We drop the six subfields that did not exist throughout the 40-year duration of our study period as well as one subfield for which we are not able to obtain the full data, leaving us with 33 subfields within theoretical mathematics. Next, we adopt the Borjas and Doran (2012) ranking of the remaining 33 subfields, which is based on the degree to which Soviets contributed to a particular subfield. They construct their rank by calculating the ratio of Soviet-to-American publications in the subfield over the period 1984-1989 and define a publication as Soviet if at least one author has a Soviet institutional affiliation. They similarly define American publications. We list the 33 subfields and their rank in Table 1.

Although we use the Borjas and Doran (2012) ranking throughout the paper, we also show in Appendix Table 2 that the main results are robust to an alternate measure. While broadly similar, this alternative measure differs on three dimensions. First, this measure defines a publication as Soviet based on author name data rather than author affiliation data.[2] Second, this measure compares Soviet publication output relative to the rest of the world rather than relative to US-only publication output. Third, this measure uses ratios based on data from 1970 to 1989 rather than from 1984 to 1989. In the end, the rankings

[2] We identify Soviet last names based on conversations with experts and documented rules regarding Soviet surname endings. We then test and calibrate our algorithm by manually looking up and verifying if academics identified as having Soviet last names were indeed Soviets.

are reasonably similar, with a Spearman Rank Correlation Coefficient of 0.84, and the qualitative results are unchanged.

4.3 Data Processing

In our main specifications, we drop all Soviet publications from the sample. We define Soviet publications as those with at least one Soviet author. We do this to avoid potential confounding effects. After 1990, not only was Soviet knowledge set free to contribute to global advancements in mathematics, but collaboration restrictions were also lifted for Soviet mathematicians. By excluding publications with at least one Soviet author, we account for the possibility of increased co-authorship rates due to removing the constraint previously preventing collaboration with Soviets.[3]

After dropping Soviet publications, our sample includes 563,462 publications spanning the 41-year period. We focus on a comparison between the three top (Soviet-rich) and bottom (Soviet-poor) ranked subfields, which represents 133,497 publications, as our main specification; however, we show the results are robust to alternative definitions of Soviet-rich: 1) top three ranking subfields relative to all others, 2) top five ranking subfields relative to all others, 3) top ten ranking subfields relative to all others, and 4) a continuous measure that relies on variation within the 33 ranked subfields of theoretical mathematics. We provide descriptive statistics in Table 2.

5 Results

5.1 Main Result: Disproportionate Increase in Team Size in Soviet-Rich Subfields After 1990

We report the estimated coefficients of Equation 1 in Table 3. We present our main specification in Column 1. The key result is the estimated coefficient on the interaction term $SovietRich_i \times AfterIronCurtain_t$, which is positive and statistically significant. This implies that the difference in average team size between papers in Soviet-rich versus -poor subfields is greater after the shock than before.

We do not present estimates of the main effects of $SovietRich_i$ or $AfterIronCurtain_t$ because we drop these terms from the estimating equation due to the year and subfield fixed

[3]Our results remain robust when adding Soviet authors back to the sample (Appendix Table 3).

effects. Also, we cluster our standard errors by subfield. We cluster to address the possibility that shocks experienced in each of the 33 subfields may be correlated, both within subfield and over time (Bertrand, Duflo, and Mullainathan, 2004; Donald and Lang, 2007).

This main result is robust to various definitions of Soviet-rich. In the first three columns, we define Soviet-rich as the top three, five, and ten subfields and Soviet-poor as all other subfields. The point estimates decrease in magnitude as we broaden the definition of Soviet-rich, which is not surprising since the difference between Soviet-rich and -poor is less stark, but the point estimates remain positive and significant. In the last column, we employ a continuous rank measure of Soviet-rich/poor, assigning the most Soviet-rich field a rank of 33 and the least a rank of 1. The coefficient remains positive, though significance is lost in the continuous specification.

Next, we examine the timing of this effect, to demonstrate that there was no underlying trend toward increased collaboration in Soviet-rich relative to -poor fields before 1990. For example, perhaps the scholars in Soviet-rich fields were better positioned to leverage the diffusion of electronic communication technology that led to increased scientific collaboration starting in the 1980s (Agrawal and Goldfarb, 2008). In this case, one might worry that the effect of lowered collaboration costs, although spread out over many years and during a slightly earlier period than the 1989-1991 events in the Soviet Union, could explain the result.

To check for such a possibility, we examine the timing of the relationship between the collapse of the Soviet Union and changes in the relative team size in Soviet-rich versus poor subfields. Specifically, we run a similar regression to the one shown in Table 3, Column 1; however, we replace the single interaction $SovietRich_i \times AfterIronCurtain_t$ with a sequence of dummy variables representing each year interacted with $SovietRich$.

We present the results in Figure 3. Each point represents the coefficient value on the covariate $Year \times SovietRich$ and thus describes the relative difference in collaboration rates between Soviet-rich and -poor fields in that year. The bars surrounding each point represent the 95% confidence interval. All values are relative to the base year of 1970. We also present these results in table form in the appendix. The most notable insight from Figure 3 is that the difference between team sizes in Soviet-rich and -poor fields was stable between 1971 and 1990. Then, starting in 1990, the difference in average team size began to increase, as evidenced by the higher coefficients. The difference in team size became statistically significant after about eight years and then continued to increase for the twelve remaining years in the sample.

5.2 Evidence that the Collapse of the Soviet Union Generated a Knowledge Shock

Next, we provide evidence consistent with our interpretation of this result being driven by a change in the knowledge stock, rather than some other factor, such as a change in the level of competition for jobs or journal slots due to the influx of Soviet mathematicians to the United States. To document that the collapse of the Soviet Union did in fact generate a knowledge shock, we turn to citation data. The intuition is that if the lifting of publication restrictions did indeed shift the knowledge frontier outwards and more so in Soviet-rich fields, then this should be observable through (non-Soviet) researchers in Soviet-rich subfields disproportionately increasing their propensity to cite Soviet prior art after 1990.[4]

To accomplish this, we collect data on references for a subsample of our data. Specifically, we collect backward citation data for papers from the top three and bottom three subfields that were published in one of the top 30 journals of mathematics (as measured by Thomson Reuters' impact factor). We further restrict the data to a window of four years before and after the collapse of the Soviet Union (1988-1993) for tractability (this data collection process is manual). We extract 1,217 publications that meet these criteria and are authored by non-Soviet scholars.

Next, we search for these publications in the Web of Knowledge reference database maintained by Thompson Reuters. We find full text information on 1,012 papers for which we extract the list of references. We count references to Soviet prior art and calculate the percentage of Soviet references relative to the total number of references. We define a citation (prior art) as Soviet if at least one of the authors had a Soviet last name as identified by our name algorithm. We check the robustness of our finding by using an alternative definition, where we define a citation as Soviet if it was published in a Soviet journal.

We use these data to estimate a difference-in-differences linear regression, similar to the one estimated in Section 5.1 above, but this time employing a measure of citations to Soviet prior art as the dependent variable:

$$SovietArt_{it} = \beta(SovietRich_i \times AfterIronCurtain_t) + Subfield_i + \gamma_t + \epsilon_{it} \quad (2)$$

[4]To be clear, this evidence does not rule out increased competition in the labor market as an alternative explanation. An increase in competition for jobs due to an influx of mathematicians in Soviet-rich subfields might result in an increase in team size and also be associated with an increase in citations to Soviet prior art as scholars also take advantage of this newly available source of knowledge. However, a failure to find evidence of an increase in citations to Soviet prior art would make it difficult to interpret the prior findings as being driven at least partly by a Soviet shock to the knowledge frontier. That said, we do present data in Section 5.4 concerning evidence of a disproportionate increase in the average team size in Japan, a nation that did not experience a notable influx of Soviet mathematicians, as evidence consistent with our interpretation but not consistent with the alternative explanation of increased competition in the labor market.

We report our estimated coefficients in Table 4. In Column 1, we define $SovietArt_{it}$ as a count of the number of references to Soviet citations (defined by journal affiliation) by academic paper i published in year t. The estimated coefficient on the interaction $\beta(SovietRich_i \times AfterIronCurtain_t)$ is positive and significant, implying that researchers publishing in Soviet-rich fields disproportionately increased their propensity to cite Soviet prior art after 1990, relative to those publishing in Soviet-poor fields. Furthermore, this disproportionate increase is driven by Soviet-rich papers with disproportionately higher team sizes after the collapse of the Soviet Union (Table 5). This suggests that the papers that most increased team size were closest to the change in the knowledge frontier.

Next, we show that this result is robust to multiple definitions of Soviet prior art. In Column 2, we define the dependent variable as the percentage of citations to papers published in Soviet journals relative to the total number of references. In Column 3, we define the dependent variable as a count of references to papers that have at least one Soviet author identified using our last name algorithm, and in Column 4, the dependent variable is the percentage of papers that have at least one Soviet author. The main result persists, though we lose statistical significance in Column 4.

Thus, the Soviet-rich subfields appear to have experienced a knowledge shock after the fall of the Soviet Union. Citations to S oviet papers increased substantially, even by non-Soviet authors.

5.3 Evidence of Specialization

Next, we provide further analysis consistent with our interpretation of the main result as evidence consistent with the knowledge burden hypothesis. In particular, we document an increase in researcher specialization (or, conversely, a decrease in diversification) in Soviet-rich subfields relative to Soviet-poor subfields after the fall of the Iron Curtain.

For this subsection, we switch the unit of analysis to the author-year and examine the degree of diversification for authors who published in a given year. We measure diversification using an author-level count of the number of sub-classification areas (as defined by the AMS in their MSC schema) that were used in the authors' publications over the previous five years. Each of the 33 subfields in our data has a large number of sub-classifications.

If the shock to the knowledge frontier does indeed lead to increased specialization, then we expect to observe a disproportionate decline in the number of sub-classifications for authors in Soviet-rich relative to -poor fields after 1990. First, we examine all authors, observing authors multiple times if they publish more than once. Then, we examine junior authors only by looking at the degree of specialization for each author exactly five years after their first publication. Thus, junior authors each appear just once in the data. We analyze juniors separately because they represent a somewhat cleaner test. Specifically, by comparing the early research of scholars who began publishing after the collapse of the Soviet Union with the early research of scholars who entered the field earlier, we examine the degree of specialization in the years of more rapid knowledge accumulation. Specifically, for author a in year t, we estimate:

$$DegreeOfDiversification_{at} = \alpha(SovietRich_a \times AfterIronCurtain_t) + Subfield_a + \gamma_t + \epsilon_{ia} \quad (3)$$

We define degree of diversification as the number of sub-classifications in which the author published over the previous five years.

Table 6 shows a disproportionate decrease in diversification for authors who published in Soviet-rich fields after the fall of the Soviet Union. Or, stated differently, we find evidence of a disproportionate increase in specialization for authors who published their work in Soviet-rich subfields. The second column shows that the average number of primary classification codes and sub-codes in which Soviet-rich authors published decreases by 7% more than for Soviet-poor authors after 1990. Even after adding author fixed effects and thereby looking at changes in specialization within individuals over time, the effect is a still significant 1% decrease. Furthermore, the results hold if we focus on junior authors only, although we cannot estimate author fixed effects here because (by construction) we observe junior authors once. When comparing the degree of specialization of pre- and post-1990 junior scholars, we find that post-1990 junior scholars from Soviet-rich subfields were disproportionately more specialized than juniors from Soviet-poor subfields. The average number of primary classification codes and sub-codes in which Soviet-rich juniors published shows a 6% decrease relative to Soviet-poor juniors after the collapse of the Soviet Union.

5.4 Knowledge Burden vs. Competition in Labor Markets

Borjas and Doran (2012, 2013a, 2013b) emphasize the labor market impact of increased competition from Soviet scholars. Increased competition also may explain the observed increase in collaboration in mathematics after the fall of the Soviet Union since the influx of Soviet mathematicians to American and European universities resulted in increased competition for jobs and journal slots. In order to present results consistent with the knowledge burden explanation but not with the increased competition explanation, we turn to a setting that experienced the knowledge shock but did not experience a significant labor market shock. Specifically, we focus on Japan, a country with no documented evidence of Soviet immigration in mathematics (Dubois et al, 2011) and which consistently ranks in the top ten in mathematics research (Dubois et al, 2011). We recognize that the labor market for mathematicians is to some extent global. In other words, even though Soviet mathematicians did not migrate en masse to Japan, it's plausible that, for example, American mathematicians who were displaced by Soviets moved to Japan, causing a sharp increase in labor supply leading to more collaboration. We find no evidence of this in our data. However, we do show a disproportionate team size increase in Japanese journal publications in Soviet-rich relative to -poor subfields after 1990. This finding is consistent with the knowledge burden hypothesis, identified separately from the alternative explanation of labor market impact due to an influx of Soviet scholars.

We start by identifying all Japanese journals in our data. We do so based on journals' documented affiliation information. Next, we distinguish between those Japanese journals included in Thomson Reuters' impact factor ranking and those that are not. The fact that Japan ranks highly in mathematics research overall raises concerns that some Japanese journals might be of international interest. Specifically, some journals might have been of interest to Soviet scholars located elsewhere. We identify Japanese journals ranked by Thomson Reuters in terms of impact factor as journals of potential international interest.

We use our main difference-in-differences specification (1) to estimate the effect of the knowledge shock on team size in Soviet-rich versus -poor fields in the Japanese setting by restricting the data to the subset of publications from Japanese journals. We provide separate estimates for publications in all Japanese journals, publications in ranked Japanese journals, and publications in not-ranked Japanese journals. We draw this subset from the set of publications in mathematics, which already excludes all publications involving Soviet scholars. Tables 7, 8 and 9 provide strong support for a disproportionate increase in team size for scholars publishing in Japanese journals, ranked or not.

6 Discussion and Conclusion

We report evidence that an outward shift in the knowledge frontier is associated with a subsequent increase in research team size and researcher specialization. Importantly, this evidence is consistent with the knowledge frontier explanation but not the other explanations for the widely documented increase in team size. In other words, although this evidence is not intended to (and does not) rule out the possibility that the other explanations also play a role, it suggests that the knowledge frontier hypothesis is a plausible explanation for at least some of the observed increase in team size in science.

In our setting, a back-of-the-envelope calculation indicates that the knowledge frontier effect accounts for 24% of the increase in team size in Soviet-rich fields in theoretical mathematics. We calculate this as follows: team size in Soviet-rich fields increased by 33%, from 1.34 to 1.78, in the before versus after period. We estimate that the Soviet-rich fields experienced an 8% disproportionate increase (relative to Soviet-poor) during this period (Table 3, Column 1). This represents 24% of the overall percentage increase. While this rough calculation can be seen as a lower bound because it assumes none of the increase in Soviet-poor subfields was due to an outward shift in the knowledge frontier, we resist this interpretation because of the numerous other assumptions underlying the 24% value.

More broadly, it is important to clarify the limitations of our test of the knowledge burden hypothesis. First, we test a particular implication of the knowledge burden hypothesis: the impact of a sudden outward shift in the knowledge frontier on collaboration and specialization. An underlying assumption of this interpretation of our estimates is that the team size response to a shock is similar to that for a gradual outward shift in the knowledge frontier. However, that may not be the case. Researchers may be able to absorb gradual increases in the knowledge frontier in a manner that does not generate as high returns to collaboration as those resulting from a sudden shock that may be more costly for researchers to internalize. Thus, our empirical results may not measure the impact of a gradual shift in the knowledge frontier.

Second, there may have been other impacts of the collapse of the Soviet Union on the field of mathematics. Borjas and Doran (2012, 2013a, 2013b) emphasize the labor market impact of increased competition from Soviet scholars. This increased competition also may have driven an increase in collaboration if, for example, returns to collaboration increased due to reasons such as risk mitigation (diversification of research projects). While we view our results on Japanese publications, citations to Soviet prior art, and specialization as more consistent with the knowledge burden hypothesis, we cannot definitively reject the possibility that changing labor markets also played a role.

Third, we focus on one particular field: mathematics. Adams et al (2005) show that mathematics is somewhat of an outlier in team size relative to other disciplines in having relatively small teams. In the first year of their study, 1981, mathematics publications had the fewest number of authors (of 12 fields). Furthermore, mathematics had the lowest annual growth rate in team size from 1981 to 1990 and the second lowest from 1990 to 1999.

In contrast, physics and astronomy had the highest growth rates, which likely was at least partly driven by the increasing role of capital-intensive equipment (e.g., particle accelerators) in those fields. Therefore, even if 24% is a reasonable lower-bound estimate of the fraction of the percentage increase in team size caused by an outward shift in the knowledge frontier in mathematics, it may be an overestimate in fields where capital equipment plays a more central role.

Overall, we document that the knowledge shock caused by the exogenous collapse of the Soviet Union led to a disproportionate increase in collaboration among non-Soviet researchers in those subfields in which Soviet mathematicians were strongest relative to other subfields of theoretical mathematics. Our examination of citations to Soviet prior art, specialization, and team sizes in Japan provides further evidence consistent with the burden of knowledge hypothesis: a knowledge shock leading to increased specialization and collaboration. In a series of papers (2009, 2010, 2011), Jones presents a variety of interventions that are potentially welfare-enhancing in the presence of a knowledge frontier effect. These include subsidies and rewards to incentivize entry into research careers, team-based evaluation of grant applications, and national or regional subsidies and specialization to prevent poverty traps due to underinvestment in human capital from coordination failures arising from thin markets for complementary skills. Although our study offers no means by which to comment on the suitability of these interventions to particular policy settings, the evidence we present here does suggest that the knowledge frontier effect is worthy of further research and possibly policy attention.

REFERENCES

Acemoglu, Daron, Hassan, Tarek A., Robinson, James A. 2011. Social Structure and Development: A Legacy of the Holocaust in Russia. Quarterly Journal of Economics, 126(2), 895-946.

Adams J.D., Black, G.C., Clemmons, J. R., Stephan P. E. 2005. Scientific Teams and Institutional Collaborations: Evidence from U.S. Universities, 1981-1999. Research Policy, 34 (3), 259-285.

Agrawal, A., Goldfarb, A. 2008. Restructuring Research: Communication Costs and the Democratization of University Innovation. American Economic Review, 98(4), 1578-1590.

Borjas, G. J., Doran, K. B. 2012. The Collapse of the Soviet Union and the Productivity of American Mathematicians. The Quarterly Journal of Economics, 127(3), 1143-1203.

Borjas, G. J., Doran, K. B. 2013a. Cognitive Mobility: Native Responses to Supply Shocks in the Space of Ideas. The Journal of Labor Economics, forthcoming.

Borjas, G. J., Doran, K. B. 2013b. Which Peers Matter? The Relative Impacts of Collaborators, Colleagues and Competitors. Working paper, University of Notre Dame.

Dubois, P., Rochet, JC., Schlenker, M. 2013. Productivity and Mobility in Academic Research: Evidence from Mathematicians. Scientometrics, forthcoming.

Fons-Rosen, Christian. 2012. Knowledge Flows through FDI: The Case of Privatisations in Central and Eastern Europe. Working paper, Universitat Pompeu Fabra.

Ganguli, I. 2012. Saving Soviet Science: The Impact of Grants When Government R&D Funding Disappears. Working paper, Stockholm School of Economics.

Graham, L. R. 1993. Science in Russia and the Soviet Union: A Short History. Cambridge University Press.

Graham, L. R., Dezhina, I. 2008. Science in the New Russia: Crisis, Aid, Reform. Indiana University Press.

Grossman, J. W. 2002. The Evolution of the Mathematical Research Collaboration Graph. Congressus Numerantium, 158, 201-212.

Hesse, Bradford W., Sproull, Lee S., Kiesler, Sara B., Walsh, John P. 1993. Returns to Science: Computer Networks in Oceanography. Communications of the ACM, 36(8), 90-101.

Jones, B. 2009. The Burden of Knowledge and the Death of the Renaissance Man: Is Innovation Getting Harder? Review of Economic Studies, 76(1), 253-281.

Jones, B. 2010. As Science Evolves, How Can Science Policy? NBER Innovation Policy and the Economy, 11,103-131.

Jones, B. 2011. The Knowledge Trap: Human Capital and Development, Reconsidered. NBER Working paper 14138.

Jones, B., Olken, B.A. 2005. Do Leaders Matter? National Leadership and Growth Since World War II. Quarterly Journal of Economics,120(3), 835-864.

Kim, E.H., Morse, A., Zingales, L. 2009. Are Elite Universities Losing Their Competitive Edge? Journal of Financial Economics, 93(3), 353-381.

Merton, R. K. 1973. The Sociology of Science: Theoretical and Empirical Investigations. University of Chicago Press, Chicago.

Mowery, D., Nelson, R., Sampat, B., Ziedonis, A. 2004. Ivory Tower and Industrial Innovation. Stanford University Press.

Newman, M. E. J. 2004. Coauthorship Networks and Patterns of Scientific Collaboration. Center for the Study of Complex Systems and Department of Physics, University of Michigan, Ann Arbor.

Oettl, Alex. 2012. Reconceptualizing Stars: Scientist Helpfulness and Peer Performance. Management Science, 58(6), 1122-1140.

Polyak, B.T. 2002. History of Mathematical Programming in the USSR: Analyzing the Phenomenon. Mathematical Programming, 91, 410-416.

Rosen, S. 1981. The Economics of Superstars. American Economic Review, 71(5), 845858.

Tikhomirov, V. M. 2007. On Moscow Mathematics - Then and Now. Golden Years of Moscow Mathematics, Second edition, co-publication of the AMS and the London Mathematical Society.

Singh, J., Fleming, L. 2010. Lone Inventors as Sources of Break-Through: Myth or Reality? Management Science, 56(1), 4156.

Sonnenwald, D. H. 2007. Scientific Collaboration. Annual Review of Information Science and Technology, 41(1), 643-681.

Stephan, P. 2012. How Economics Shapes Science. Harvard University Press.

Stuen, E.T., Mobarak, A.M., Maskus, K.E. 2012. Skilled Immigration and Innovation: Evidence from Enrollment Fluctuations in US Doctoral Programmes. Economic Journal, 112(565), 1143-1176.

Waldinger, F. 2010. Quality Matters: The Expulsion of Professors and the Consequences for PhD Student Outcomes in Nazi Germany. Journal of Political Economy, 118(4), 787-831.

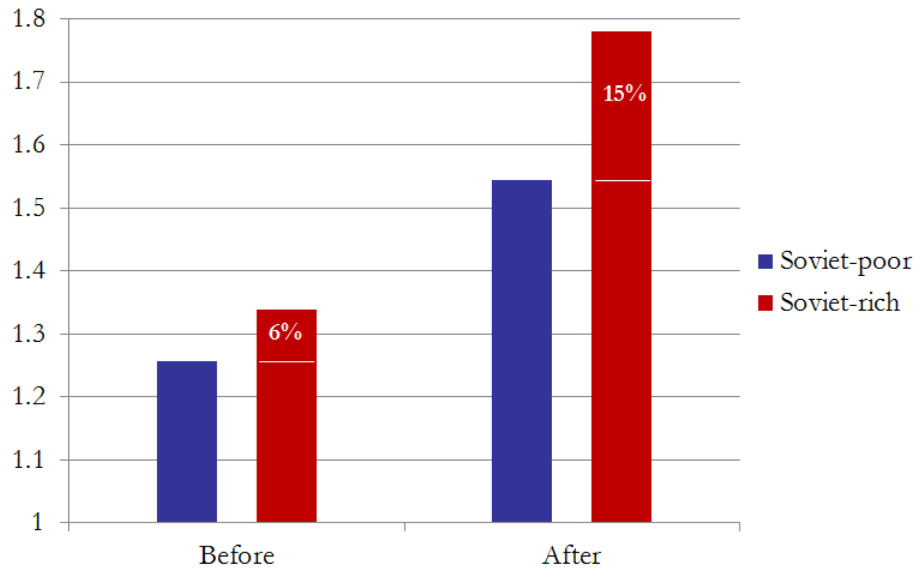
Waldinger, F. 2012. Peer Effects in Science – Evidence from the Dismissal of Scientists in Nazi Germany. Review of Economic Studies, 79(2), 838-861.

Walsh, J. P., Bayma, T. 1996. Computer Networks and Scientific Work. Social Studies of Science, 26(3), 661-703.

Wuchy, S., Jones, B., Uzzi, B. 2007. The Increasing Dominance of Teams in Production of Knowledge. Science 316, 1036.

Zucker, L. G., Darby, M. R. and Brewer, M. B. 1998. Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises. American Economic Review, 88(1) 290306.

Figure 1: **Disproportionate increase in mean team size in Soviet-rich subfields after 1990**



Notes: We base this figure on 40 years of publication data for the three top and three bottom ranked subfields of theoretical mathematics. Each point on the graph represents the coefficient value on the covariate $Year \times SovietRich$ and thus describes the relative difference in collaboration rates between Soviet-rich and -poor fields in that year. The bars surrounding each point represent the 95% confidence interval. All values are relative to the base year of 1970. We also present these results in table form in Appendix Table 2.

Figure 2: **Mathematics Taxonomy**

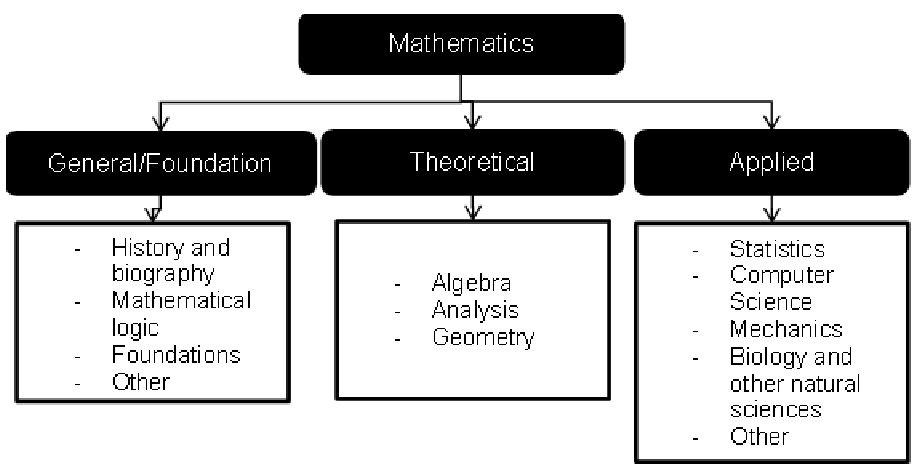
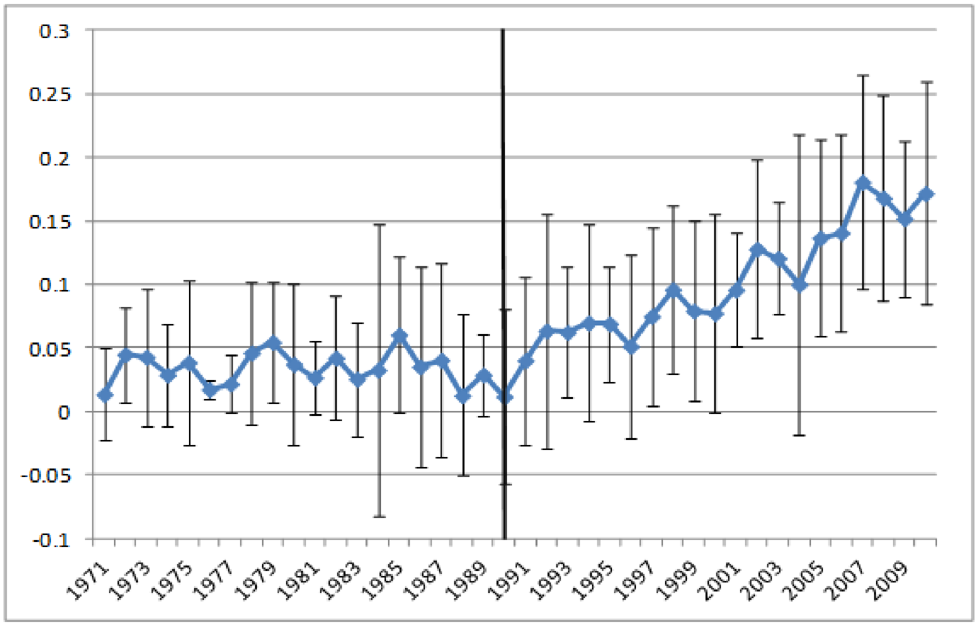


Figure 3: **Plot of estimated coefficients on interaction between Soviet-rich and year (DV = Team Size)**



Notes: We base this figure on 40 years of publication data for the three top and three bottom ranked subfields of theoretical mathematics. Each point on the graph represents the coefficient value on the covariate $Year \times SovietRich$ and thus describes the relative difference in collaboration rates between Soviet-rich and -poor fields in that year. The bars surrounding each point represent the 95% confidence interval. All values are relative to the base year of 1970. We also present these results in table form in Appendix Table 2.

Table 1: **Subfield rank based on proportion of Soviet publications (1984-1989)**

Subfield Rank as per Borjas and Doran (2012)	**MSC**	**Theoretical mathematics category**	**Description**
1	45	Analysis	Integral equations
2	42	Analysis	Fourier analysis
3	35	Analysis	Partial differential equations
4	40	Analysis	Sequences, series, summability
5	31	Analysis	Potential theory
6	49	Analysis	Calculus of variations and optimal control; optimization
7	44	Analysis	Integral transforms, operational calculus
8	30	Analysis	Functions of a complex variable
9	8	Algebra	General algebraic systems
10	39	Analysis	Difference equations and functional equations
11	47	Analysis	Operator theory
12	17	Algebra	Non-associative rings and non-associative algebras
13	41	Analysis	Approximations and expansions
14	58	Geometry	Global analysis, analysis on manifolds
15	32	Analysis	Several complex variables and analytic spaces
16	33	Analysis	Special functions
17	22	Algebra	Topological groups, lie groups, and analysis upon them
18	54	Geometry	General topology
19	20	Algebra	Group theory and generalizations
20	28	Algebra	Measure and integration
21	18	Algebra	Category theory; homological algebra
22	55	Geometry	Algebraic topology
23	26	Algebra	Real functions, including derivatives and integrals
24	52	Geometry	Convex geometry and discrete geometry
25	14	Algebra	Algebraic geometry
26	43	Analysis	Abstract harmonic analysis
27	15	Algebra	Linear and multilinear algebra; matrix theory
28	6	Algebra	Order theory
29	12	Algebra	Field theory and polynomials
30	5	Algebra	Combinatorics
31	51	Geometry	Geometry
32	57	Geometry	Manifolds
33	13	Algebra	Commutative rings and algebras

Notes:We adapt this ranking from Borjas and Doran (2012) and base it on the ratio of the number of Soviet versus American papers published in the particular subfield between 1984 and 1989. We define papers as Soviet if at least one author has a Soviet institutional affiliation. We similarly define American papers.

Table 2: **Descriptive Statistics**

	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
All Observations					
Log of author count	0.342	0.425	0	2.89	563,462
After Iron Curtain	0.625	0.484	0	1	563,462
Soviet Rich (top 3)	0.169	0.374	0	1	563,462
After Iron Curtain x Soviet Rich (top 3)	0.121	0.326	0	1	563,462
Soviet Rich (top 5)	0.183	0.386	0	1	563,462
After Iron Curtain x Soviet Rich (top 5)	0.128	0.334	0	1	563,462
Soviet Rich (top 10)	0.287	0.452	0	1	563,462
After Iron Curtain x Soviet Rich (top 10)	0.194	0.395	0	1	563,462
Top and bottom three fields only					
Log of author count	0.362	0.428	0	2.19	133,467
After Iron Curtain	0.678	0.467	0	1	133,467
Soviet Rich	0.711	0.453	0	1	133,467
After Iron Curtain x Soviet Rich	0.511	0.500	0	1	133,467
Count of Soviet references by name	0.811	1.528	0	12	1,012
Percent of Soviet references by name	0.046	0.084	0	0.6	1,012
Count of Soviet references by journal	0.295	0.881	0	12	1,012
Percent of Soviet references by journal	0.015	0.047	0	0.5	1,012
Count of subfields (all authors)	2.039	1.705	1	47	315,161
Log of count of subfields (all authors)	0.490	0.613	0	3.850	315,161
Count of subfields (junior authors)	1.931	1.471	1	26	41,282
Log of count of subfields (junior authors)	0.463	0.580	0	3.258	41,282

Table 3: **Teams in Soviet-rich subfields exhibit a disproportionate increase in team size after 1990**

	Dependent variable: log of author count				
	Top and bottom 3 subfields	**Soviet-rich defined as top 3 of subfields**	**Soviet-rich defined as top 5 of subfields**	**Soviet-rich defined as top 10 of subfields**	**Continuous**
AfterIronCurtain x SovietRich	0.0780***	0.0489***	0.0394***	0.0389**	0.0011
	(0.0117)	(0.0106)	(0.0138)	(0.0152)	(0.0011)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.113	0.106	0.106	0.106	0.106
Observations	133,497	563,462	563,462	563,462	563,462

Notes: The unit of analysis is the publication. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%

Table 4: **Teams in Soviet-rich subfields exhibit a disproportionate increase in propensity to cite Soviet prior art after 1990**

	Dependent variable: References to Soviet art			
	Count of Soviet references (Defined by Soviet journal)	**Percentage of Soviet references (Defined by Soviet journal)**	**Count of Soviet references (Defined by name)**	**Percentage of Soviet references (Defined by name)**
AfterIronCurtain x SovietRich	0.4020***	0.0172***	0.4496**	0.0135
	(0.0423)	(0.0036)	(0.1345)	(0.0086)
Year fixed effects	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes
R-squared	0.117	0.180	0.131	0.094
Observations	1,012	1,012	1,012	1,012

Notes: The unit of analysis is the publication. The sample includes the top/bottom three subfields drawn from the top 30 journals four years before and after the collapse of the Soviet Union. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%

Table 5: **The disproportionate increase in references to Soviet prior art is driven by larger-sized teams in Soviet-rich subfields**

	Dependent variable: References to Soviet art			
	Count of Soviet references (Defined by Soviet journal)	**Percentage of Soviet references (Defined by Soviet journal)**	**Count of Soviet references (Defined by name)**	**Percentage of Soviet references (Defined by name)**
AfterIronCurtain x SovietRich x LogAuthorCount	0.5628***	0.0167***	1.1321***	0.0347**
	(0.1078)	(0.0029)	(0.2682)	(0.0092)
AfterIronCurtain x SovietRich	0.1416	0.0097**	-0.0509	-0.0010
	(0.0832)	(0.0037)	(0.2185)	(0.0109)
AfterIronCurtain x LogAuthorCount	0.0558**	0.0033	0.0023	0.0014
	(0.0197)	(0.0024)	(0.0935)	(0.0069)
SovietRich x LogAuthorCount	-0.2472**	-0.0122***	-0.5491	-0.0227
	(0.0922)	(0.0017)	(0.3602)	(0.0160)
LogAuthorCount	0.0412	0.0002	0.0194	-0.0125
	(0.0787)	(0.0007)	(0.2734)	(0.0114)
Year fixed effects	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes
R-squared	0.128	0.084	0.141	0.103
Observations	1,012	1,012	1,012	1,012

Notes: The unit of analysis is the publication. The sample includes the top/bottom three subfields drawn from the top 30 journals four years before and after the collapse of the Soviet Union. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%

Table 6: **Authors in Soviet-rich subfields exhibit a disproportionate increase in specialization**

	All authors; Top and bottom three subfields only				**Junior authors only (at 5 years since first publication)**	
	Dep. Var is Count of subfields	**Dep. Var is Logged count of subfields**	**Dep. Var is Count of subfields**	**Dep. Var is Logged count of subfields**	**Dep. Var is Count of subfields**	**Dep. Var is Logged count of subfields**
AfterIronCurtain x	-0.2135***	-0.0709***	-0.0311**	-0.0112*	-0.1306***	-0.0609***
SovietRich	(0.0334)	(0.0111)	(0.0145)	(0.0065)	(0.0339)	(0.0127)
SovietRich	-0.4174***	-0.1608***	N/A	N/A	-0.2305***	-0.0927***
	(0.0325)	(0.0108)			(0.0269)	(0.0097)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	No	No	Yes	Yes	Yes	Yes
R-squared	0.028	0.030	0.010	0.010	0.085	0.082
Observations	315,161	315,161	280,427	280,427	41,282	41,282

All models are OLS with robust standard errors, clustered by author. *significant at 10%, **significant at 5%, ***significant at 1%
Note: Author specialization (or negative generalization) is measured by a count of distinct codes published over the last five years. We interpret fewer distinct codes as more specialized. Thus, a negative estimated coefficient implies that the covariate is positively correlated with specialization.

Table 7: **Teams in Soviet-rich subfields exhibit a disproportionate increase in team size after 1990 (all Japanese journals)**

	Dependent variable: log of author count				
	Top and bottom 3 subfields	**Soviet-rich defined as top 3 of subfields**	**Soviet-rich defined as top 5 of subfields**	**Soviet-rich defined as top 10 of subfields**	**Continuous**
AfterIronCurtain x SovietRich	0.0692***	0.0581***	0.0634***	0.0699***	0.0025***
	(0.0173)	(0.0154)	(0.0162)	(0.0150)	(0.0006)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.076	0.068	0.068	0.068	0.068
Observations	5,096	17,209	17,209	17,209	17,209

Note: The unit of analysis is the publication. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%

Table 8: **Teams in Soviet-rich subfields exhibit a disproportionate increase in team size after 1990 (ranked Japanese journals)**

	Dependent variable: log of author count				
	Top and bottom 3 subfields	**Soviet-rich defined as top 3 of subfields**	**Soviet-rich defined as top 5 of subfields**	**Soviet-rich defined as top 10 of subfields**	**Continuous**
AfterIronCurtain x SovietRich	0.0678***	0.0653***	0.0738***	0.0751***	0.0026***
	(0.0203)	(0.0175)	(0.0189)	(0.0143)	(0.0007)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.093	0.070	0.070	0.070	0.070
Observations	3,859	13,003	13,003	13,003	13,003

Note: The unit of analysis is the publication. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%

Table 9: **Teams in Soviet-rich subfields exhibit a disproportionate increase in team size after 1990 (not-ranked Japanese journals)**

	Dependent variable: log of author count				
	Top and bottom 3 subfields	**Soviet-rich defined as top 3 of subfields**	**Soviet-rich defined as top 5 of subfields**	**Soviet-rich defined as top 10 of subfields**	**Continuous**
AfterIronCurtain x SovietRich	0.0956***	0.0638*	0.0521	0.0738**	0.0033***
	(0.0206)	(0.0329)	(0.0378)	(0.0321)	(0.0011)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.101	0.109	0.109	0.110	0.110
Observations	1,237	4,206	4,206	4,206	4,206

Note: The unit of analysis is the publication. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%

APPENDIX

Table A1: **Robustness to alternative ranking measure**

	Dependent variable: log of author count				
	Top and bottom 3 subfields	**Soviet-rich defined as top 3 of subfields**	**Soviet-rich defined as top 5 of subfields**	**Soviet-rich defined as top 10 of subfields**	**Continuous**
AfterIronCurtain x SovietRich	0.0800***	0.0475***	0.0404***	0.0364**	0.0012
	(0.0126)	(0.0107)	(0.0150)	(0.0157)	(0.0010)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.112	0.107	0.107	0.106	0.106
Observations	133,497	563,462	563,462	563,462	563,462

Note: In this table, we use our own ranking measure rather than Borjas and Doran' (2012); our measure uses worldwide publications from 1970-1989 rather than US publications from 1984-1989 and relies on identifying Soviet publications by ethnicity of names rather than by affiliation data. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%.

Table A2: **Coefficient estimates used to plot Figure 3**

Dependent variable: Log of author count per publication per year Top and bottom three subfields only			
SovietRich x 1971	0.0137	SovietRich x 1991	0.0403
	(0.0139)		(0.0257)
SovietRich x 1972	0.0452*	SovietRich x 1992	0.0635
	(0.0147)		(0.0360)
SovietRich x 1973	0.0428*	SovietRich x 1993	0.0624**
	(0.0212)		(0.0200)
SovietRich x 1974	0.0290	SovietRich x 1994	0.0700*
	(0.0156)		(0.0303)
SovietRich x 1975	0.0389	SovietRich x 1995	0.0691**
	(0.0250)		(0.0178)
SovietRich x 1976	0.0174***	SovietRich x 1996	0.0513
	(0.0030)		(0.0280)
SovietRich x 1977	0.0218*	SovietRich x 1997	0.0750**
	(0.0089)		(0.0273)
SovietRich x 1978	0.0465*	SovietRich x 1998	0.0960*
	(0.0218)		(0.0259)
SovietRich x 1979	0.0550**	SovietRich x 1999	0.0792**
	(0.0187)		(0.0274)
SovietRich x 1980	0.0373	SovietRich x 2000	0.0773*
	(0.0249)		(0.0303)
SovietRich x 1981	0.0269*	SovietRich x 2001	0.0958***
	(0.0111)		(0.0175)
SovietRich x 1982	0.0422*	SovietRich x 2002	0.1279***
	(0.0190)		(0.0274)
SovietRich x 1983	0.0256	SovietRich x	0.1206***
	(0.0175)		(0.0173)
SovietRich x 1984	0.0327	SovietRich x 2004	0.1000*
	(0.0449)		(0.0461)
SovietRich x 1985	0.0604*	SovietRich x 2005	0.1376***
	(0.0239)		(0.0303)
SovietRich x 1986	0.0353	SovietRich x 2006	0.1406***
	(0.0306)		(0.0302)
SovietRich x 1987	0.0406	SovietRich x 2007	0.1806***
	(0.0294)		(0.0329)
SovietRich x 1988	0.0127	SovietRich x 2008	0.1680***
	(0.0247)		(0.0312)
SovietRich x 1989	0.0289*	SovietRich x 2009	0.1518***
	(0.0125)		(0.0239)
SovietRich x 1990	0.0119	SovietRich x 2010	0.1717***
	(0.0270)		(0.0341)
Year fixed effects	Yes	Subfield fixed effects	Yes
R-squared	0.114	Observations	133,4977

Note: Estimated with OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%

Table A3: **Robustness to including Soviet papers**

	Dependent variable: log of author count				
	Top and bottom 3 subfields	**Soviet-rich defined as top 3 of subfields**	**Soviet-rich defined as top 5 of subfields**	**Soviet-rich defined as top 10 of subfields**	**Continuous**
AfterIronCurtain x SovietRich	0.0696***	0.0424***	0.0346**	0.0283*	0.0010
	(0.0110)	(0.0108)	(0.0136)	(0.0154)	(0.0011)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Subfield fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.107	0.103	0.102	0.102	0.102
Observations	169,305	689,793	689,793	689,793	689,793

Notes: In this table, we present estimates of the main effect when including Soviet authors back into the sample. The unit of analysis is the publication. All models are OLS with robust standard errors, clustered by subfield. *significant at 10%, **significant at 5%, ***significant at 1%.